An Improved ICA Method on Resting State fMRI Data Analysis

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***Abstract*—For the resting state functional magnetic resonance imaging (fMRI) data, it has an important significance in clinical medicine to extract the functional connectivity regions (Default Mode Network, DMN). Independent component analysis (ICA) is an excellent method to detect the DMN. It has been popularly applied to the resting state fMRI data. However, ICA decomposition is realized by updating the objective function iteratively till convergence to further estimate the independent sources. The iterative process requires to a set of initial vectors which is generated by randomness. Thus the randomness of initialization brings about the randomness of the results. So the results acquired by ICA are not fixed in different decompositions. To mitigate the problem, we proposed an improved method, named ATGP-ICA, to do fMRI data analysis. The new method can generate a set of fixed initial vectors with automatic target generation process (ATGP) instead of being produced randomly. Our experimental results show that the ATGP-ICA method can not only detect the DMN network of resting state fMRI data, but also can eliminate the randomness of the classical ICA method.**

Keywords- ATGP; fMRI; ICA; ROC power analysis

I. INTRODUCTION

In 1995, Biswal et al. [1] revealed fluctuations in signal intensity in each pixel that had a physiologic origin. Time courses of low frequency (<0.1Hz) fluctuations in resting brain were observed had a high degree of temporal correlation. It could be concluded that correlation of low frequency fluctuations, which may arise from fluctuations in blood oxygenation or flow, was manifestation of functional connectivity of the resting brain. So fMRI in resting state has a wider clinical impact than task-related fMRI data. At present, it has made an achievement in clinical by exploring the resting state fMRI of Alzheimer's disease patients, epileptic, cognitive disorder patients and so on [2], [3].

Methods of analyzing fMRI data can be classified into two categories: model-driven methods and data-driven methods [4]. As to model-driven methods, these methods largely depend on the selection of Region of Interest (ROI); however, the selection of ROI needs the knowledge of anatomy as a priori. But as regarded to the resting state fMRI data, there is no experiment paradigm and any prior knowledge. Therefore, it is difficult to detect the functional connectivity with model-driven methods. In contrast, data-driven methods don't need any prior knowledge such as principle component analysis (PCA), independent component analysis (ICA), and clustering analysis (CA), which have been popularly applied to the field of signal processing because of the advantages of no need of priori knowledge.

Among the data-driven methods, ICA has been popularly used in fMRI data analysis [5], [6]. Spatial ICA can detect spatially independent component brain maps and activation time courses without any prior knowledge [6]. Thus it's suitable for explore resting state fMRI data analysis. However, ICA cannot determine the unique results in different decompositions. Independent components (ICs) are generated with random initial vectors because ICA optimizes the objective function is usually based on gradient which is stochastic. So the randomness is introduced into the results.

In order to overcome this problem, we propose a method which utilizes ATGP to generate a suitable set of initial vectors to initialize the objective function [7]. ATGP is derived from orthogonal subspace projection (OSP) which is a supervised method and applied to hyperspectral image analysis. Because of the limitation of OSP, ATGP is developed as an unsupervised and unstrained method on the basis of OSP. ATGP can produce a suitable set of initial vectors instead of being generated randomly. As a consequence, the results acquired by ICA are fixed but random.

The paper is organized as follows: firstly, the traditional ICA is reviewed. On basis of ICA, we introduce the theory of ATGP-ICA. Then we perform the experiments on the resting state fMRI data to indicate that ATGP-ICA can also detect the DMN. Furthermore, the ROC power analysis was performed on the resting state fMRI data compared to the traditional ICA. Finally, we draw a conclusion with a discussion according to the results of experiments in the last section.

II. METHODS

A. ICA Introduction

In this paper, we perform ICA analysis in the following model:

$$\boldsymbol{X}=\boldsymbol{AS} \tag{1}$$

where $\boldsymbol{X}$ is the observed dataset with M time points and N voxels, $\boldsymbol{A}$ is the mixing matrix of the spatial sources, and S is the independent sources. ICA assumes that the observed data are linearly mixed by a set of separate independent sources and demixes these signal sources according to their statistical independence. From the perspective of algorithm, the ICA model can be represented as $\boldsymbol{Y}=\boldsymbol{WX}$, where $\boldsymbol{W}$ is a column full-rank unmixing matrix and $\boldsymbol{A}=\boldsymbol{W}^{-1}$ [6]. In ICA algorithm, ICA updates $\boldsymbol{W}$ iteratively until maximum nongaussianity to make $\boldsymbol{W}$ approximate $\boldsymbol{A}^{-1}$ as far as possible, thus $\boldsymbol{Y}$ will approximate $\boldsymbol{S}$ more closely. However $\boldsymbol{W}$ is initialized with random initial vectors, introducing the randomness into the final results [9]. In this paper, we will deal with this problem to eliminate the randomness of ICA.

B. ATGP-ICA

ATGP has been successfully applied to the hyperspectral image data to realize automatic target recognition [7], end member extraction [10], [11] and dimensionality reduction [12]，while applying ATGP to fMRI data still received little attention. It can be regarded as an unsupervised and unconstrained OSP [13] technique which can find targets by performing a set of OSPs specified by

$$\boldsymbol{p}_{\boldsymbol{U}}^{\perp}=\boldsymbol{I}-\boldsymbol{U}\boldsymbol{U}^{\#} \tag{2}$$

where $\boldsymbol{U}^{\#}=(\boldsymbol{U}^{T}\boldsymbol{U})^{-1}\boldsymbol{U}^{T}$ is the pseudo-inverse of U. $^{\perp}_{\boldsymbol{U}}$ represents that the projector $\boldsymbol{p}_{\boldsymbol{U}}^{\perp}$ maps the observed voxel vector r into the orthogonal complement of <**U**>,denoted by <**U**>$^{\perp}$.The following is the step of the ATGP algorithm [8].

(1) Initial condition:

Let N is the number of the target vectors. Find the maximal gray level value $\boldsymbol{t_0}$. Set k=0;

(2) Let k=k+1 and apply $\boldsymbol{P}_{\boldsymbol{t0}}^{\perp}$ via equation (2) to all the voxels r in the image and find the kth target $\boldsymbol{t}_k$ generated at the kth stage which has the maximum orthogonal projection as follows:

$$\boldsymbol{t_k}=\arg\{\max(\boldsymbol{P}_{[\boldsymbol{U}_{k-1}\boldsymbol{t}_k]}^{\perp}\boldsymbol{r})^{T}(\boldsymbol{P}_{[\boldsymbol{U}_{k-1}\boldsymbol{t}_k]}^{\perp}\boldsymbol{r})]\} \tag{3}$$

(3) If n ($\boldsymbol{t}_0$,…, $\boldsymbol{t}_k$)<N where n(. , .) can be the number of the target vectors, then go to step 2. Otherwise, the algorithm terminated. Under this condition, the generated target pixels $\boldsymbol{t}_0$, $\boldsymbol{t}_1$, …, $\boldsymbol{t}_k$ are regarded as the desired targets.

According to the algorithm, the key idea of the ATGP is that the projection operator should perform on the whole image when a certain $\boldsymbol{t}_i$ is obtained, then finds the vector with the maximum magnitude value of the projection image. These guarantee that the same image only can generate a set of fixed initial vectors. So ATGP is used to produce the initial vectors to replace the traditional method. The detail algorithm of ATGP-ICA is described as follows:

(1) Use resample scheme to correct the sample dependence of fMRI data in conjunction with MDL proposed by Li et al. [14] to estimate the number of ICs, N.

(2) Apply the ATGP algorithm generate N target voxel vector, $\{\boldsymbol{t}_i\}_i^{p}$.

(3) Use $\{\boldsymbol{t}_i\}_i^{p}$ as the initial projection vectors to replace those randomly generated .

(4) Perform ICA on fMRI data to find N ICs, $\{\mathrm{IC}_i\}_{i=1}^{p}$.

III. EXPERIMENTS

We perform experiment on the resting state fMRI data to indicate that ATGP-ICA can also detect the functional network compared to the traditional ICA. From perspective of ICA algorithm, we choose fastICA [15] for the ICA decomposition in our experiments.

A. Resting State fMRI Data

For resting state fMRI data experiment, the BOLD fMRI data were acquired on a Philips 3.0T scanner using a multi-element receiver coil to allow partially parallel image acquisition with single-shot SENSE gradient echo EPI with 47 slices providing the whole-brain coverage and 123 volumes. The functional scans were acquired using the following parameters: TR=2.5s, scan resolution=96×96, slice thickness=3mm, in-plane resolution=2.67mm×2.67mm, and SENSE acceleration factor=2.0.

B. Data Processing

In this paper, we use SPM8 software (http://www.fil.ion.ucl.ac.uk/spm/) to carry out the data pre-processing, including slice timing, motion correction, spatial normalization and smoothing with the Gaussian kernel (FWHM=8mm).

C. Experiments Results

1) Resting state fMRI data results

As to resting state fMRI data, one subject was chosen to this experiment. The data set produces 35 ICs. Figure.1 (a) shows the DMN detected by ATGP-ICA and Figure.1 (b) shows the DMN detected by ICA. According to the Figure.3, ATGP-ICA is effective to detect the DMN of the resting state fMRI data.

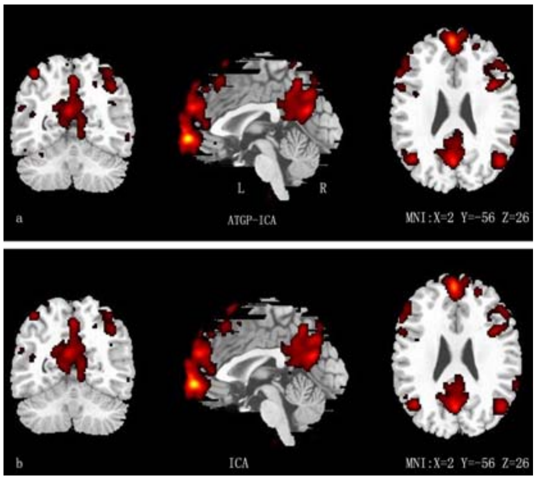

Figure.1 The DMN networks detected by the two different methods.

D. ROC Power Analysis

In section C, the experiments we performed demonstrate that ATGP-ICA is an effective method to detect the functional regions. In this section, we apply ROC power analysis to indicate that the ATGP-ICA can get fixed results in different decompositions. We decompose the resting state fMRI data 10 times with ATGP-ICA and the traditional ICA respectively. Then the components of interest are selected to further ROC power analysis.

To assess the performance of once decomposition with ATGP-ICA, we take the ROC curve analysis [16]-[18] as a measure. To compute ROC curves, firstly we should choose a reference. In this experiment, for hybrid data, the location of signal was determined as a priori which is easy to generate the reference. But as to the resting state fMRI data, the exact position of functional region is uncertain. So we use the component of interest from the first decomposition as a reference. Then we vary z-score threshold to build spatial maps. If a voxel defined as active in once decomposition was also active in the reference, we mark this voxel as a true positive. On the contrary, if a voxel is defined as active in the same decomposition but is marked as non-active in the reference decomposition, this voxel will be marked as false positive. The number of true positive voxels and false positive voxels are divided by the total number of active voxels and non-active voxels in the reference decomposition to generate the true positive rate (TPR) and false positive rate (FPR) [19]. Based on this ROC curve, the further ROC power analysis was adopted, which was denoted by the area surrounded by the ROC curve.

1) Results

Figure.2 shows the ROC power of the DMN of resting state fMRI data corresponding to the ATGP-ICA and ICA respectively. As depicted in the Figure.2, the cyan curve of ROC power is in fluctuation, which demonstrates that results of ICA decomposition were uncertain and random. Namely, once decomposition was not reliable with the traditional ICA. But according to the black curve, the ROC power values are same in different decompositions with ATGP-ICA. So in a conclusion, the resting state fMRI data also can get rid of the randomness compared to the traditional ICA. Apart from this, the signal reconstruction performance corresponding to the resting state fMRI data of ATGP-ICA almost outweighs that of the traditional ICA according to the ROC power analysis.

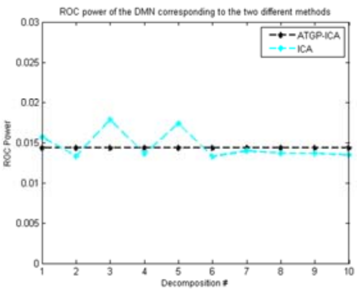

Figure.2. The ROC power of DMN of the resting state fMRI data corresponding to the two different methods. The black curve generated by the ROC power values of the DMN from 10 decompositions by ATGP-ICA. The cyan curve generated by the ROC power values of the DMN from 10 decompositions by ICA.

IV. DISCUSSION AND CONCLUSION

According to the functional maps of the resting state fMRI data shown in Figure.1, the maps can be extracted by ATGP-ICA. So we can use the initial values generated by ATGP to initialize the unmixing matrix to relieve the randomness. The advantages of this method are that no matter how many times ICA decomposes, the results are fixed. In addition, as shown in Figure.2, ATGP-ICA not only can keep the components fixed in different decomposition, but also sometimes has better performance than that of ICA. Apart from these, Figure.2 demonstrates ICs acquired by ICA is random and unreliable. For this reason, we often use repeated decomposition to replace the once decomposition. So we plan to furthermore invalidate the performance of ATGP-ICA and make a comparison with repeated decompositions with ICA. If the performance of ATGP-ICA outweighs that of repeated decompositions with ICA, ATGP-ICA can save lots of computing time and has the advantage of performance compared to repeated decompositions with ICA.

In addition, although ATGP-ICA can get the fixed order of ICs, the order of ICs is not ideal. Namely the order of the component of interest is not always in the top. We will explore further to find a set of more suitable initial projection vector to produce the ideal sort. Under this circumstance, we need not sort the ICs again because the ICs are obtained in desired order.

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